A STUDY ON MACHINE LEARNING TO REDUCE THE COMPLEXITY OF PRIDICTOR DATA IN KIDS DUE TO BIPOLAR DISORDER

PhD SYNOPSIS

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1 Area/ Specialization of Proposed Research Work

Computer Science & Engineering/Health Care/ Bipolar Disorder

2 Title of Proposed Research Work

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3 INTRODUCTION

The term "episodic" refers to a mental disorder that only manifests itself occasionally and at unpredictable intervals, and "chronic" refers to a condition that lasts for an extended period of time. It can cause changes in mood, energy, activity, and concentration or focus that are out of the ordinary, often extreme, and unpredictable. The mental illness known as bipolar disorder is also known as manic-depressive disorder. In the vast majority of cases, bipolar disorder does not manifest itself until late adolescence (the teen years) or early adulthood. Occasionally, children will exhibit symptoms of bipolar disorder. Bipolar disorder is a condition that does not go away on its own and typically requires treatment for the rest of the patient's life. It is possible for bipolar disorder to play a significant role in suicidal thoughts, the loss of a job, and conflict within a family; however, correct treatment leads to improved outcomes.

Types of Bipolar Disorder

There are three main classifications of bipolar disorder, although all of them feature extreme shifts in mood, energy, and activity. Excessive "up," elated, and energized behavior or elevated activity levels (manic episodes) are just one end of the spectrum, whereas extreme sadness, "down," hopelessness, or low activity levels are just the other (depressive episodes).

It's possible for people with bipolar illness to experience periods of normal (euthymic) mood interspersed with periods of despair. "Rapid cycling" is defined as four or more episodes of mania or depression within a year.

- **Bipolar I** Disorder is diagnosed when a manic episode lasts for at least seven days (most of the day, virtually every day) or when manic symptoms are so severe that hospital care is required.
  Separate episodes of depression, each lasting at least two weeks, are also rather common. Mixed-feature episodes of mood disturbance (exhibiting both depressive and manic symptoms) are also possible.

- **Bipolar** II **Disorder** Depressive episodes and hypomanic episodes, but not full-blown manic episodes, are characteristic of Bipolar II Disorder.
- **Cyclothymic** disorder, also known as cyclothymia, is characterized by hypomanic and depressive symptoms that persist but are not severe enough or chronic enough to be classified as hypomanic or depressive episodes. In adults, the symptoms often last for two years, but in kids and teens, they last for about a year.
- Other Specified and Unspecified Bipolar and Related Disorders refers to bipolar disorder symptoms that do not fit any of the established categories.

Symptoms of Bipolar Disorder:

Symptoms Depression Mania	
Depression	Mania
Feeling worthless, helpless or hopeless	Excessively high or elated mood
Loss of interest or pleasure (including hobbies or sexual desire)	Unreasonable optimism or poor judgement
Change in appetite	Hyperactivity or racing thoughts
Sleep disturbances	Decreased sleep
Decreased energy or fatigue (without significant physical exertion)	Extremely short attention span
Sense of worthlessness or guilt	Rapid shifts to rage or sadness
Poor concentration or difficulty making decisions	Irritabilit

4 OBJECTIVE

1. To predict a model identifying mental disorder in kids by machine learning techniques.
2. To intimate priory of complexity by regular updating the trained data.
3. To understand the family history by genome sequences, why behavioral output is working like that.
4. To resolve the error by using statistical based techniques that is incurable but giving optimal output.

5 HYPOTHESIS

- Sadness, irritability, clinginess, concern, aches and pains, refusal to go to school, and underweight are all possible indicators of depression in young children..

6 LITERATURE REVIEW

Both men and women have a 1% lifetime risk of developing bipolar disorder, a severe mood condition [1, 2]. Chronic mood swings are a hallmark of this disorder, which is also linked to a high risk of disability and suicide. The lifetime risk for someone who is not connected to anybody else with bipolar illness is between 0.5 and 1.5%, whereas the risk for someone who is a first-degree relative with BD is between 5-10%, and the risk for a monozygotic co-twin with BD is between 40-70% [3, 4]. It's a major reason people can't work everywhere in the world, and the solutions to the problem are inadequate. Researchers have shown that genes have a major role in BD susceptibility and that this has been demonstrated via investigations of families, twins, and adoptees [5].

According to twin studies based on data from the UK hospital record and the Finnish population registry, the heritability estimates are 89% and 93%, respectively [6]. The genetic basis of this phenomenon is still poorly known [7–11]. For the first episode, environmental stress is more likely to play a role in the beginning, while subsequent episodes are less attributable to environmental factors [12, 13]. Antioxidants inhibit the oxidation process which leads to the creation of free radicals. Lysosomal peroxidation is the source of these free radicals. Oxygen free radicals (reactive oxygen species - ROS) may trigger autophagy, apoptosis, and necrosis when present in high enough concentrations [14], and they can also disrupt the integrity of other biomolecules including DNA when present in low enough concentrations [15]. Due to its increased susceptibility to oxidative damage, the brain has been linked to the etiology of neuropsychiatric disorders [16].

It is widely acknowledged that Big Data is a major driving factor in the development of new technologies and the expansion of the global economy. The data is analyzed to gain insight and improve services through cutting-edge methods such as the smart grid, e-health system, social network, etc. Concerns about personal privacy arise at every stage of data processing, including transmission, mining, and aggregate. More efficient and potentially revealing mining techniques are being developed. Concerns about privacy have produced workable explanations for meeting privacy requirements.

The goal is to find a balance between sharing too much information and getting enough out of these services, often known as utility. Scholars have proposed new solutions to these problems in recent years [17]. In order to keep data private in the age of big data, it is important to explore privacy-related factors while the associated research is still in its infancy. An array of perspectives on privacy in the context of big data analysis are presented in this illuminating chapter [18].

With the advent of social networks, outsourced cloud computing, the Internet of Things (IoT), and data transfer, vast data has been created, making Big Data a pervasive technology. Massive data volume, high data velocity, and rich data diversity are all hallmarks of the data explosion that we're seeing [19]. Big Data is made possible by the remarkable use of networking between smart things and the intelligent computational platform, but this comes with certain privacy concerns in settings where users' physical whereabouts, financial transactions, and behavioral patterns are all recorded digitally [20, 21].

Today, most hospitals use electronic systems for keeping track of their patient's medical histories, which raises privacy issues [22]. Most advanced businesses nowadays [23] use Big Data to monitor their workers by keeping tabs on their activities online and in the office. Disparities in healthcare and business have shed light on the disjuncture between existing privacy regulations and the realities of Big Data and the urgent need for new laws to address all of the associated privacy problems [24–33].

7 RESEARCH METHODOLOGY

In order to achieve the above mentioned objectives, the following methodology will be

Followed:

First, we will conduct a comprehensive literature review of scholarly articles published in peer-reviewed journals of international renown, as well as papers presented at conferences, workshops, symposia, and technical reports, and other online resources and materials that pertain to the various classification methods.

Second, to identify a child's emotional shifts, use a variety of machine learning algorithms such Multivariate Pattern Analysis, Multiple Kernel Learning, Support Vector Machine, K-means Algoritham, Relevance Vector Regression, and Cross Validation.

Third, develop and improve new methods of detecting bipolar disorder in children, as well as refine existing methods, and identify appropriate methods of classification and diagnosis.

Fourth Assess the efficacy of current methods for detecting bipolar disorder in young people. Fifth, evaluating how the modified method performs in comparison to the standard procedure. Inferences will be drawn from the outcomes of experiments and presented at conferences and in academic articles.

8 DATA ANALYSIS

There are a number of statistical tests that may be run to confirm whether or not the offered remedies are effective and proper. Information points are required for data analysis; today's primary sources of information come from electronic medical records (EMRs), claims, and registries maintained by healthcare providers and insurance companies. Data collected from patients' active monitoring, passive monitoring of Internet and smartphone use, and sensor data may soon be combined with the EMR.

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